Chapter 1
Artificial Intelligence for Healthcare Logistics: An Overview and Research Agenda

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Abstract In this chapter we present the existing literature on machine learning approaches and artificial intelligence for logistical problems arising for designing, providing and improving healthcare services. As a basis, we provide a framework for the classification of artificial intelligence. For the analysis, we distinguish between the care levels (primary, secondary and tertiary care), the planning levels (strategic, tactical and operational), as well as the user types (doctors, nurses, technicians, patients, etc.). Based on the results, we provide a research agenda with open topics and future challenges.

1.1 Introduction

The techniques of *machine learning* (ML) and *artificial intelligence* (AI) are omnipresent in today's academic discussions [1]. In this chapter, we aim to shed light on the capabilities of artificial intelligence for the area of healthcare logistics, a promising field in operations research [2]. Based on a literature review [3], we explore three different aspects of interest to reveal existing research as well as future possibilities. First, an overview of the care levels [4], i.e. *primary*, *secondary* and *tertiary* care and existing as well as future AI applications in this dimension requires analysis. Second, the aspect of planning—distinguished into *strategic*, *tactical* and *operational* levels—is of interest [5]. Finally, we regard the user types of the healthcare logistic services [6], e.g. *doctors*, *technicians* or *patients* and possible enhancements of their tasks with AI. Therefore, we contribute to the body

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of knowledge by providing a holistic overview of AI in healthcare logistics and derive a research agenda to highlight priorities in future research endeavours in this highly important field.

This work focuses only on approaches applied to healthcare logistics, i.e. planning problems arising for logistical tasks, e.g. in hospitals or other care institutions. That is, AI for medical applications, e.g. to determine the probability for a certain disease, is excluded from this work.

The remainder of this work is structured as follows: we first set the required nomenclature as a basis by summarising the concepts of machine learning and artificial intelligence in Sect. 1.2. With the necessary definitory framework at hand, we review the aspects of care levels, the planning levels as well as the user types in Sect. 1.3. We then categorise the existing literature in Sect. 1.4, synthesise our findings within a holistic overview and derive a research agenda accordingly. We conclude with recommendations, a summary and limitations in Sect. 1.5.

1.2 Machine Learning and Artificial Intelligence

As a basis for our classification of related work and the resulting research agenda, we first review the different notions and concepts of machine learning and artificial intelligence within extant literature. In addition, we come up with a working definition of artificial intelligence for the remainder of this work.

Machine learning and artificial intelligence are related, often present in the same context and sometimes used interchangeably [7]. While the terms are common in different communities, their particular usage and meaning vary widely—especially with the rise of AI research within the past decade [8].

1.2.1 Machine Learning

Within the field of computer science, machine learning has the focus of designing efficient algorithms to solve problems with computational resources [9]. While machine learning utilises approaches from the field of statistical learning [10], it also includes methods that are not entirely based on previous work of statisticians—resulting in new and well-cited contributions to the field [11–13]. Recently, especially the method of deep learning raised increased interest [14], as it has drastically improved the capabilities of machine learning, e.g. in speech [15] or image recognition [16].

In its basic form, machine learning describes a set of techniques that are used to solve a variety of real-world problems with the help of computer systems that can learn to solve a problem instead of being explicitly programmed [17]. In general, we can differentiate between supervised, unsupervised and reinforcement learning [18, 19]. *Supervised learning* comprises methods and algorithms to learn the mapping from the input to the output. For instance, letting a child sort toy cars and telling the child in advance there are sports cars and SUVs, the child would perform a supervised learning task. It would learn to recognise patterns from the regarded cars (input) and sort them accordingly (output). *Unsupervised learning*, however, comprises methods and algorithms that are able to reveal previously unknown patterns in data. In the example discussed before, letting a child sort toy cars and letting the child determine how to arrange/cluster them would be an unsupervised learning task. In demarcation from supervised learning, *reinforcement learning* differs in the fact that correct input/output combinations need not be presented, and sub-optimal actions need not be explicitly corrected. Instead the focus is on finding a balance between the exploration of uncharted solutions and the exploitation of already achieved knowledge [20]. In case of the child sorting toys, this would mean he or she would (sometimes) receive feedback ("rewards") on the nature of its decisions, which allows it to slowly build up additional knowledge. In the field of operations research, reinforcement learning is also called *approximate dynamic programming* [21], or *neuro-dynamic programming* [22].

1.2.2 Artificial Intelligence

The topic of artificial intelligence (AI) is rooted in different research disciplines, such as computer science, philosophy, or futures studies [7]. In this work, we mainly focus on the field of computer science, as it is the most relevant one in identifying the contribution of AI to the field of healthcare logistics. AI research can be separated into different research streams [23]. These streams differ on the one hand as to the objective of AI application—thinking vs. acting, and on the other hand, as to the kind of decision-making—targeting a human-like decision vs. an ideal, rational decision. Especially the research stream of "Rational Agents" considers an AI as a rational [23] or intelligent [24] agent. This stream is the most relevant for the remainder of this work, as it describes the implementation of AI as intelligent agents within real-world environments.

Machine learning plays three major roles in this field of artificial intelligence. First, machine learning is relevant in the implementation of intelligent agents, precisely in the back-end layer of such agents. When regarding the case of supervised and reinforcement machine learning, we need to further differentiate between the process task that is building (equivalently training) adequate machine learning models [25] and the process task that is executing on the knowledge from these models [26]. Therefore, the "thinking layer" of agents is typically defined by machine learning models [7].

Second, the learning back-end in the intelligent agent dictates if and how the agent is able to learn, e.g. which precise algorithms it uses, what type of data processing is applied, how concept drift [27] is handled, etc. Russel and Norvig [23] regard two different types of intelligent agents: *simple-reflex agents* and *learning agents*. This differentiation considers whether the underlying models in the thinking layer are once trained and never touched again ("simple-reflex agent") or continuously updated and adaptive (“learning agent”). In the recent literature, suitable examples for both can be found [28–30].

Third, it is of interest how automated the necessary process steps are for an AI. Every machine learning task involves various process steps, including data source selection, data collection, pre-processing, model building, evaluating, deploying, executing and improving [31]. The autonomy and the automation of these tasks are of particular interest, especially the necessary human involvement for the AI to execute [7].

1.2.3 Working Definition

Synthesising the results from the previous two sections, we depict our definitory framework of AI in Fig. 1.1. We differentiate on the different process tasks of data analysis, recommendation and decision/action for any AI endeavour. *Data analysis* includes all necessary steps of pre-processing and automated generation of predictions based on new, incoming data—typically based on machine learning. The task of *recommendation* describes the interpretation of the results from the previous task. For instance, an AI might just deliver outputs on whether or not a certain ambulance service will make it in time to the hospital. The more advanced step would be to output recommendations, e.g. using a different available ambulance service that could arrive more promptly. Finally, the last process task is making a *decision* and possibly *act* on it. In the previous example, this would mean the dispatching of a different ambulance. We differentiate which of these tasks the AI handles and which is handled by humans, resulting in the three levels of *AI-Enrichment*, *AI-Enhancement* and *AI-Autonomy*.

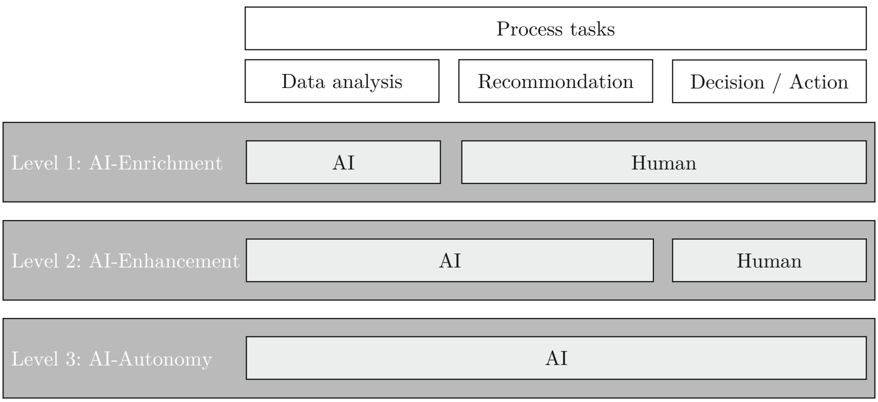

Fig. 1.1 Levels of AI involvement for different process tasks

1.3 Framework for Healthcare Logistics Literature

The review of prior literature is an integral part of any research project, as a comprehensive overview allows the necessary foundations for advancing knowledge. Furthermore, it allows to uncover research gaps, where additional work is needed. According to Webster and Watson [3], one of the most used literature review methods [32], each review of the existing body of knowledge is separated into multiple steps.

The first step deals with the collection of articles. The collected articles must reflect the research topic in its entirety. The search should not be limited to a specific journal, geographical area or research method. However, one typically starts to search for relevant articles in leading specialist journals. These then serve as a starting point for a *forward–backward search*. The *backward search* is the search for further relevant literature from the cited sources of the articles in question. The *forward search* is the search for the literature that quotes the present article by searching the article, e.g. via the "Web of Science".

In the second step, the selected literature is analysed. This is done concept—and not author—related, because the review article should be based on ideas and concepts and not on people. The identification of research gaps, the lack of essential concepts in the review and the use of the article as a summary of the existing literature for further research articles are thus facilitated. A concept matrix facilitates the sorting of the relevant articles by categorising the articles according to defined variables, analysis levels, etc.

Third, Webster and Watson recommend the elaboration of gaps in research. They also recognise that this is the most difficult part of a literature analysis. A concept model with supporting propositions is considered to be the methodology for the development of this task. They point out that this model and its propositions gain importance only through the justification of the relationship between the chosen variables.

Finally, the last step deals with the evaluation, conclusion and discussion of the obtained results.

In the following, a framework for classifying the published literature is developed. It bases on three dimensions: planning levels, care levels and user types. These three aspects are first defined separately and then combined into one framework.

1.3.1 Planning Levels

Healthcare logistics can be divided into the three planning levels: strategic, tactical and operational (Fig. 1.2). While strategic decisions are usually made for years or even decades, tactical decisions can be revoked on a yearly or monthly basis. Operational planning happens daily, often as offline decisions, or in real-time usually with online approaches.

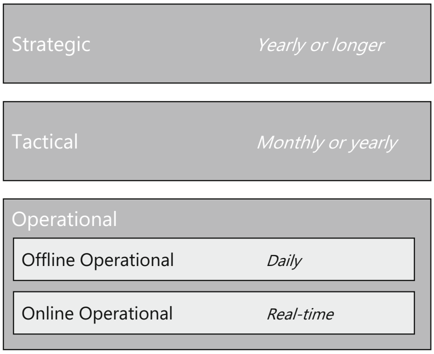

Fig. 1.2 Planning levels in healthcare logistics

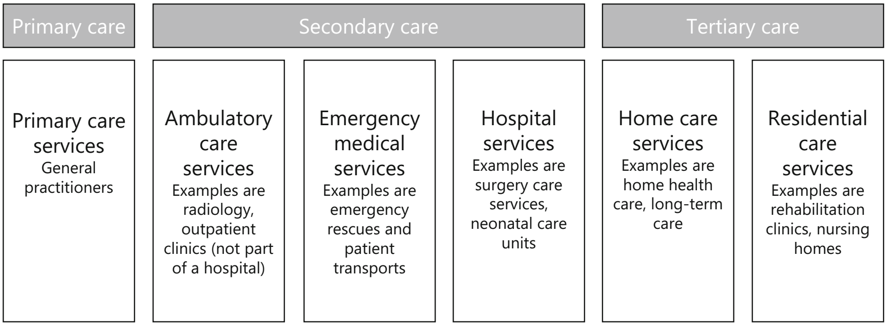

Fig. 1.3 Levels of medical care

1.3.2 Care Levels

In general, we differentiate between primary, secondary and tertiary care (Fig. 1.3). Secondary care includes ambulatory care services, emergency medical services and hospital services. Tertiary care consists of home care services and residential care services. Hulshof et al. [33] have proposed a similar structure and used it to categorise existing research for planning problems in healthcare for which operations research literature has been published.

1.3.3 User Types

In healthcare logistics, users of AI approaches could be manifold due to the nature and design of the underlying service network and its contributors and participants. This includes multiple stakeholders, precisely:

- the patient who receives treatment,
- insurance companies who might pay for the service,

- relatives who desire to be informed and might do part of the care at home,
- hospital staff, including
  - managers,
  - doctors (general practitioners and specialists),
  - nurses,
  - medical information scientists,
  - laboratory staff,
  - physiotherapists,
  - transport services,
  - IT.
- emergency medical services, including
  - dispatchers,
  - paramedics,
  - drivers,
  - relief organisations,
- as well as the government (e.g. health ministries and other policy-makers).

A framework would not be useful if all possible user types were included. Also, not all users have been targeted in the literature. Therefore, we distinguish the following three user types in our framework:

- Patients: Individuals who receive medical care from providers.
- Providers: Institutions or people that provide care to patients and charge payers for that care. We divide this type again into two subgroups:
  - Hospital management, and
  - doctors and nurses.
- Payers: Institutions that pay providers for healthcare services, which include insurance carriers, private employers and the government.

1.3.4 Framework

Figure 1.4 shows the framework that we will use to structure the literature on AI applied to healthcare logistics that is based on the one introduced by Hulshof et al. [33]. The overall four user types are abbreviated by P1–P3, with P1 meaning patients, P2.1 hospital management, P2.2 doctors and nurses, and P3 payers. References are included with their respective number [X].

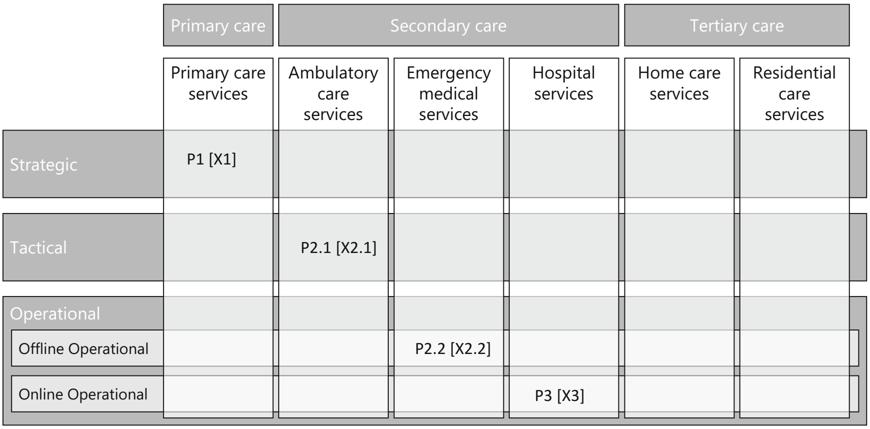

Fig. 1.4 Framework for sorting the literature on AI in healthcare logistics

1.4 Literature Review

As described in the previous section, we performed a literature analysis with Google Scholar, using the search strings as shown in Fig. 1.5.

When scanning the literature, we classified papers on AI for healthcare in five main categories:

1. Publications that apply AI to medical problems, e.g. to determine the probability for a certain disease, the probability that a certain treatment will be successful or survival predictions, e.g. in the intensive care unit (ICU) [34, 35]. Examples of commonly studied areas include stroke prediction [36], infections, diabetes, e.g. personalisation of diabetes therapy [37] or predicting hospital readmissions for diabetics [38], and cancer. Machine learning approaches can predict rehabilitation potential [39]. Researched topics also include AI-based decision support systems for personalised medicine and treatment [40] as well as trends in telemedicine with AI [41]. Neural networks can be used to predict future illnesses that can be of interest for insurance companies to determine expected costs [42]. In addition, several AI approaches have been proposed for

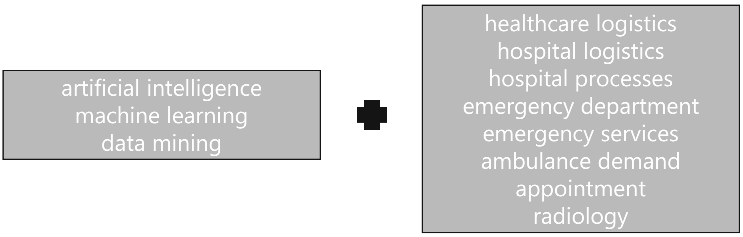

Fig. 1.5 Search strings used for the literature review

radiotherapy. For example, AI can be applied for radiology [43] or radiotherapy treatments to determine patient-specific dosing [44]. The majority of publications are patient-centred with a decision support focus on doctors.

2. Especially in the USA, AI approaches are applied to the scanning of medical claims and the detection of fraud. These approaches are especially relevant for insurance companies and hospital management.
3. Several review papers within the interplay of analytical techniques and healthcare have been published—each focusing on a different topic, e.g. AI capabilities [45, 46], data mining [47–53], big data in general [54], business intelligence [55], as well as a systematic mapping study [56], healthcare organisational decision-making [57] and specific reviews on big data and machine learning in radiation oncology [58] or artificial intelligence for neonatal care [59].
4. One of the two relevant categories for this work are publications in which AI methods are used to predict input for healthcare logistics problems, e.g. predicting demand for healthcare services like ambulances [60], surgery durations or no-shows [61].
5. In the last category, publications embed AI into optimisation approaches for healthcare logistics problems, e.g. as part of a heuristic.

In our search, we identified 132 papers to be relevant for this work based on the title and the keywords. After having read the papers, we discarded 81 papers. We derived two relevant main categories: AI for optimisation input (34 papers) as well as AI for healthcare logistics optimisation (17 papers)—both of which will be regarded in detail in the following.

1.4.1 AI for Optimisation Input

Menke et al. present an artificial neural network (ANN) to predict the patient volume arriving at an emergency department (ED) [62]. The authors state that the ANN can be used for this task, but it must be properly designed and include all relevant variables. Then, it can be used as an input for staffing the ED appropriately, aiming at shorter waiting times for patients as well as lower or more balanced workloads for the doctors and nurses. Afilal et al. propose time series-based forecasting models to predict long-term as well as short-term arrival rates at the emergency department [63]. Also Xu et al. target the prediction of daily arrivals at the ED [64], especially considering non-critical patients. They investigate an artificial neural network (ANN) to study the contributing variables and daily arrival rates. They compare it with the non-linear least square regression (NLLSR) and the multiple linear regression (MLR). Acid et al. use different algorithms for learning Bayesian networks to predict arrivals at the ED [65].

Besides the overall patient volume, predicting the admission rates is another important problem arising for emergency departments that can be addressed by machine learning approaches. Graham et al. compare three machine learning approaches: logistic regression, decision trees and gradient-boosted machines (GBM) for predicting hospital admissions from the ED [66]. The authors find that GBM leads to the highest accuracy, while logistic regression should be chosen when interpretability is most important. Having good estimates for admission rates can improve patient flow and help schedule resources. Krämer et al. use supervised machine learning techniques to classify hospital admissions into urgent and elective care [67]. Patient disposition decisions are predicted by Lee et al. [68]. They distinguish four admission classes: intensive care unit, telemetry unit, general practice unit and observation unit, and test three different machine learning approaches for the classification.

Length of stay (LOS) is one of the main ED performance indicators. Benbelkacem et al. test and compare several machine learning approaches for predicting a patient's LOS, for example based on date and hour [69].

Cai et al. choose a Bayesian network to develop a model for real-time predictions of length of stay, mortality and re-admission for hospitalised patients based on ED data [70].

In order to prioritise patients' admission to the hospital, Luo et al. test logistic regression, random forest, gradient-boosting decision tree, extreme gradient boosting and combination of all four approaches [71].

For a hospital, patient re-admissions are a big challenge. Machine learning methods can help detect patients with a high re-admission probability. Turgeman and May combine a boosted C5.0 tree, as the base classifier, with a support vector machine (SVM), as a secondary classifier [72]. Zheng et al. study classification models that use neural networks, random forest and support vector machines for hospital re-admissions, with a specific focus on heart failure patients [73]. A clinical tool based on machine learning for predicting patients who will return within 72 h to the paediatric emergency department was developed by Lee et al. [74]. Futoma et al. compare predictive and deep learning models for 30 day re-admissions [75]. The re-admission problem is also studied by Rana et al. [76], Eigner et al. [77] and Wickramasinghe et al. [78].

Beds in ICUs are often scarce resources. Then, it is important to timely discharge patients to a regular ward when possible. McWilliams et al. test two machine learning classifiers, a random forest and a logistic classifier, to detect patients who can be discharged from the ICU [79].

Padoy envisions a decision support tool for workflow recognition during surgery using machine learning approaches, more specifically deep learning [80]. He proposes to use video input, e.g. laparoscopic videos, to automatically determine the current phase of the surgery.

Funkner et al. use a decision tree approach for predicting clinical pathways in a hospital [81].

Al Nuaimi presents four models based on naive Bayes, k-nearest neighbour, and SVM to predict the healthcare demand in Abu Dhabi, i.e. a district's current and future needs for hospitals and clinics [82].

No-shows play an important role for appointment planning, in hospitals as well as private practices. Topuz et al. present a Bayesian belief network for predicting paediatric clinic no-shows [83]. Nelson et al. try to predict no-shows for scheduled magnetic resonance imaging appointments using logistic regression, support vector machines, random forests, AdaBoost and gradient-boosting machines [84]. Goffman et al. apply logistic regression models to predict no-shows and appointment behaviour in the Veterans Health Administration [85]. Harris et al. combine regression-like modelling and functional approximation, using the sum of exponential functions, to predict patient no-shows [86]. A hybrid probabilistic model based on multinomial logistic regression and Bayesian inference to predict the probability of no-show and cancellation in real time was developed by Alaeddini et al. [87]. Goldman et al. apply a multivariate logistic regression analysis to predict the no-show rate in primary care [88]. Kurasawa et al. predict no-shows for clinical appointments by diabetic patients [61].

Due to high-cost pressures in many healthcare systems, it is crucial for hospitals to avoid unnecessary high spending. Accordingly, Eigner et al. propose to use machine learning approaches to identify high-cost patients [89].

Outside of hospitals, several publications have used machine learning approaches to predict the demand for emergency medical services (EMS), i.e. ambulances. Good predictions can be used as input for ambulance location and relocation approaches to reduce response times. Spatio-temporal predictions for 1-h intervals and 1 km^2 with three methods based on Gaussian mixture models, kernel density estimation and kernel warping are proposed by Zhou [90]. Chen and Lu test moving average, artificial neural network, linear regression and support vector machine to predict emergency services demand [91]. Chen et al. apply moving average, artificial neural network, sinusoidal regression and support vector regression to the same problem [60]. Villani et al. focus on forecasting pre-hospital diabetic emergencies that have to be served by an Australian EMS provider, using the seasonal autoregressive integrated moving average (SARIMA) modelling process [92].

Curtis et al. studied the applicability of machine learning models to predict waiting times at a walk-in radiology facility as well as waiting times for patients with scheduled appointments at radiology facilities [93]. The authors test and compare many different machine learning algorithms, including neural network, random forest and support vector machine.

In Fig. 1.6, the publications are inserted into the framework.

1.4.2 AI for Healthcare Logistics Optimisation

Arnolds and Gartner propose a machine learning-based clinical pathway mining approach for hospital layout planning [94]. The machine learning algorithm builds on the probabilistic finite state automata (PFSA) to learn significant clinical pathways. The pathways are then one input for the mathematical model to determine a hospital layout. In their case study, the determined layout reduces distances travelled by patients significantly.

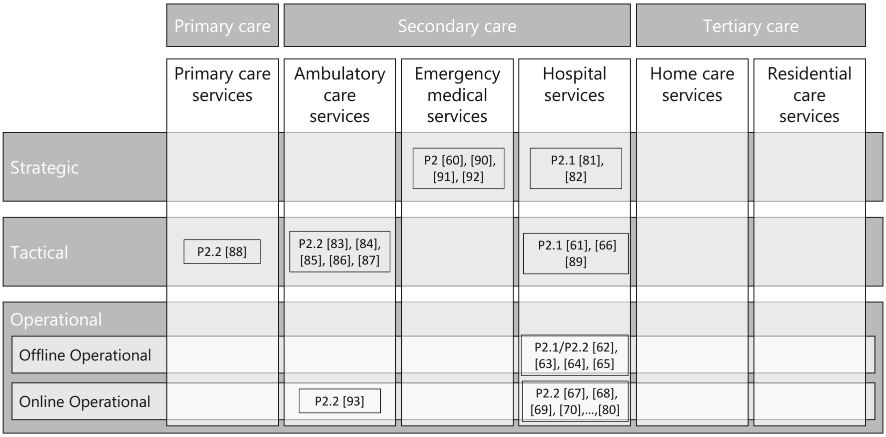

Fig. 1.6 Overview of publications on AI for optimisation input

Gartner et al. use ML methods for predicting and classifying diagnosis-related groups [95]. They incorporate the methods into an MIP-based resource allocation model. They showed that their approach could improve diagnosis-related group (DRG) classification both before and during the admission of a patient. The optimised allocation of resources such as operating rooms and beds allowed an additional 9% of elective patients to be admitted.

Alapont et al. discuss the design and the use of a data mining tool for hospital management, based on algorithms that are implemented in Weka [96]. They connect logistical problems like bed management, surgery scheduling and resource allocation to machine learning-based predictions of bed occupation, hospital admission rates and emergencies, for example.

Also Srikanth and Arivazhagan propose to use machine learning approaches for demand prediction in order to improve hospital resource allocations and patient schedules [97]. They present a patient inflow prediction model based on a resilient back-propagation neural network, which improves the prediction accuracy.

Again with the aim of improving the allocation of resources in a hospital, Aktaş et al. developed a decision support system that contained a Bayesian belief network [98].

In order to improve processes in an emergency department, Laskowski combines an agent-based model with a machine learning approach to a hybrid system for decision support [99].

Ceglowski et al. combine a data-mining approach with a discrete-event simulation in order to analyse processes in an emergency department and to identify bottlenecks in the interface between the ED and the hospital wards [100].

Thompson et al. summarise and discuss artificial intelligence for radiation oncology [101]. Besides clinical decision support, image segmentation and dose optimisation, they also mention the importance of and potential gains for logistical problems like staffing and resource allocation.

Lofti and Torres present a predictive model to be used in scheduling patients in an urban outpatient clinic [102]. They use decision tree methods to determine the likelihood of a patient's no-show and test the results in a scheduling algorithm.

Patient no-shows also play an important role in the work of Srinivas and Ravindran [103]. The authors developed a prescriptive analytics framework to schedule patient appointments for a family medicine clinic. Machine learning was used to classify patients based on their no-show risk. Improving patient satisfaction was one of the main aims.

Harper presents a framework for machine learning approaches like decision trees with healthcare optimisation models to improve healthcare processes and resource utilisation [104].

An ambulance location approach using predicted future emergency locations by an artificial neural network was published by Grekousis and Liu [105]. In order to do so, they introduced new concepts and notions to model emergency events as sets of interconnected points in space that create paths over time.

Two further publications do not explicitly match the focus of this chapter but present very interesting approaches. The first uses data mining and machine learning in the context of disaster and crisis management [106]. The authors state that the approaches allow to address a wider spectrum of problems, such as situational awareness and real-time threat assessment using diverse streams of data. The second presents an ML-based approach for automatic stress detection in emergency phone calls to support dispatching of ambulances and help call takers distinguish important and critical calls in case of high workloads [107].

In addition to the previously discussed papers, we found three additional, rather recent, works that present promising optimisation approaches with embedded machine learning methods.

Potter develops two machine learning-based greedy heuristics to improve the assignment of patients to the available treatment machines in radiotherapy [108]. Strahl aims at reducing waiting times and surgeon idle time in an outpatient clinic [109]. He uses supervised learning regression to predict appointment durations and surgeon arrival times in a scheduling approach, a greedy hill-climbing algorithm, to improve the existing schedule. Letzner proposes supervised machine learning approaches for predicting hospital selection when a patient is picked up by an ambulance [110]. The performance of random forest, logistic regression and neural network are compared.

In Fig. 1.7, the publications are inserted into the framework.

1.4.3 AI for ED Logistics

We now want to take a closer look at one exemplary area in healthcare logistics for using AI. The overview shows that comparably many publications target

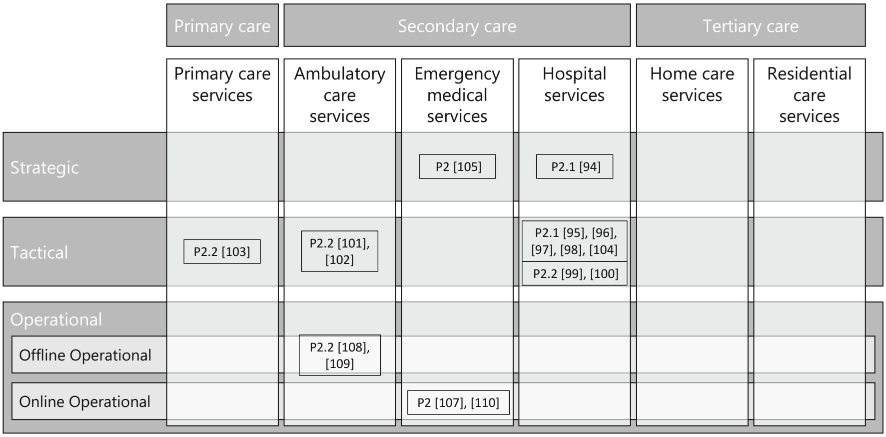

Fig. 1.7 Overview of publications on AI for healthcare logistics optimisation

emergency departments. Crowding is becoming a challenging issue for many hospitals worldwide. The main uncertainties for ED and hospital managers are the arrival rates of patients, together with their necessary treatments and treatment times, as well as the probabilities for patients being admitted to the hospital. Out of the 12 ED-related papers in this review, three predict arrival rates or ED volume [62–64], and one predicts re-arrivals at the ED [74], two consider patients' admission from ED [66, 67], one studies more concretely disposition from ED [68], two target LOS [69, 70] and three more generally ED management [65, 99, 100]. Eight papers only use a single machine learning approach, altogether four papers use two [64], three [66] or four [68, 69] different approaches and compare the results. The 12 papers apply 14 different machine learning approaches altogether, whereas artificial neural networks and logistic regressions are used in three publications, support vector machines and decision trees are studied twice. Random forest, for example, is used in one paper. The variety of approaches used makes it difficult to draw general conclusions on which approach to use for which problem. Future research could investigate this question and study methods in detail, preferably using different data sets, as data items used in the publications also differ significantly. While most use patient arrival times and dates, some use patient-related data like age and gender or case-related data items like the triage score and treatment durations, while others also use external data items like weather. Overall, we counted more than 25 input parameters.

1.4.4 Synthesis and Research Agenda

Accurate predictions are basically important for all planning problems in healthcare for which the input is not completely deterministic—which is hardly ever the case in reality. This is true for all care levels, planning levels and user types. The prediction types and levels that are necessary at different planning levels vary. While it might be sufficient for an emergency services provider to know the average daily occurrence of emergencies in the next years when locating the bases at the strategic level, on the operational level a precise prediction for ambulance demand in the next hour is of interest. This often leads to the fact that different (machine learning) methods must be tested and deployed for predicting demand, service times or other inputs at the three planning levels. Predicting demand at one level might be easier than at another.

Most of the publications included in this study focus on one care level and one planning level, while it would be interesting and promising to test the approaches also for other care and planning levels. Then, many of the "gaps" in Figs. 1.6 and 1.7 can be easily filled. Resulting research questions for machine learning and artificial intelligence should also address the transferability of approaches between providers.

Future research has the potential to address previously untapped potential in the application of AI for healthcare management and the optimisation of healthcare logistics, including medical predictions and personalised treatments. As a next step, the question arises how predictions can be incorporated best into existing processes like scheduling an assignment of resources—as so far, research in this area is still rare.

Most of the approaches have only been presented and tested in theory so far. Hardly any were actually included in decision support systems and deployed in practice. Arising research questions include (1) *How well do the predictions perform in practice?* and (2) *What is the quality of the optimisation approaches that are based on or make use of AI?*

1.5 Conclusion

In this chapter we have presented a framework for classifying the literature on AI applied to healthcare logistics. The framework integrates care levels, planning levels and user types.

Figures 1.6 and 1.7 show the publications inserted into the framework.

While the majority of papers we came across used machine learning approaches for medical purposes, more and more publications address healthcare logistics and management problems. The literature overview shows that applying artificial intelligence and especially machine learning methods to healthcare logistics problems is a promising approach. A few areas have already been addressed by several publications, including appointment planning, (patient) scheduling and resource utilisation. Machine learning methods have been successfully developed to predict demand for emergency departments, the ICU or ambulances, for example.

Certain limitations apply to the presented research. The quality of our systematic literature review is assessed based on a set of quality assessment criteria as introduced by Kitchenham et al. [111]. Inclusion and exclusion criteria are described in detail in Sect. 1.4. In terms of the coverage of our study, we used all literature that Google Scholar provided us for our search terms. Regarding the assessment of the quality and validity of the analysed literature, we did not assess the validity of the studies, for example by journal rankings or citations, as our aim was of exploratory nature. Furthermore, the extracted knowledge from scientific literature is always liable to the specific scientific environment, e.g. there can be biases in the methods that were used [112].

Another challenge we faced when searching the literature was a missing clear definition of machine learning and artificial intelligence methods. While authors always named the method they applied, not all papers used the terms “machine learning” or “artificial intelligence”, making it harder to find and to classify them. In this work, we included all papers that either used at least one of the two terms or applied a method that can be categorised as AI by common understanding as well as our own introduced understanding of the terms.

Based on the literature overview, three areas for future research were detected. The first is studying the transferability of existing approaches to other care and planning levels as well as to providers on the same levels. The second addresses the need to further include machine learning and artificial intelligence approaches into healthcare management and optimisation of planning problems, also making use of already existing AI methods. The third area regards the actual deployment of AI methods in practices, potentially integrated into decision support systems.

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